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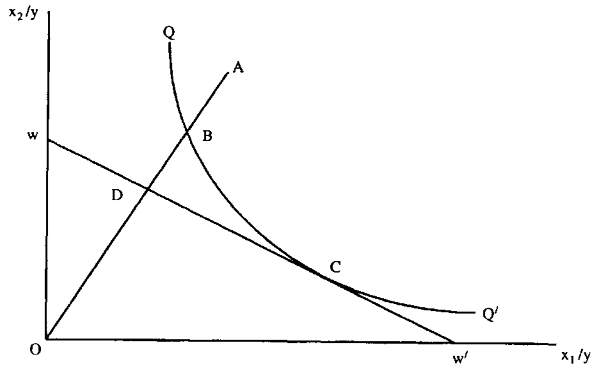

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Productive efficiency of the swine industry in Hawaii

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Summary

Hawaii's swine industry has experienced a continuous decline in recent years. Both the number of farms and the number of hogs have significantly decreased since 1985. This decline, which is primarily attributed to high production costs, especially feed costs, limited land availability, price competition from imported live hogs, and increased environmental concerns, has raised serious concern among all industry participants for the long-term survival of the industry. Improving profitability and productive efficiency will be key determinants of the future of Hawaii's swine industry.

This study therefore examines the future potential of the industry by determining operational efficiency based on farm-level costs of and returns from swine production collected from 60 commercial swine producers in Hawaii during the fall of 1994. Analysis of costs and returns showed a negative net return for many producers, especially among medium and small producers. On average, large producers were more profitable because they paid less for purchased feed, used less labor per unit of pork produced, and weaned more pigs/sow/year than medium and small producers. Improving profitability will be key to the survival of individual producers as well as the economic viability of the industry. One way to improve profitability is to produce more from given resources and technology, i.e., to improve productive efficiency.

This study examined various productive efficiencies for a sample of swine producers in Hawaii using stochastic production frontier and data envelopment analysis (DEA). Technical, allocative, and economic efficiencies were computed by estimating a stochastic Cobb-Douglas production frontier. Pure technical, scale, and overall technical efficiencies were derived by solving input-oriented and output-oriented DEA models. The relationship between the efficiency estimates and various farm-specific factors was examined. Finally, the study also examined the role of productive efficiency on farm profitability as well as on the industry's potential for reducing costs and increasing production.

Based on the stochastic production frontier, the average technical, allocative, and economic efficiency scores for Hawaii's swine industry were 70.4, 76.0, and 53.1%, respectively. Based on the input-oriented DEA results, average pure technical, scale, and overall technical efficiency scores were 74.8, 84.2, and 63.5%, respectively. Corresponding values for the output-oriented DEA were 72.6, 89.5, and 64.4%. Although there was no significant difference between the technical efficiency estimate from the stochastic frontier and pure technical efficiency estimates from DEA models, the stochastic technical efficiency estimate was significantly higher than the DEA overall technical efficiency estimate.

There was a significant and positive relationship between farm size and efficiency. Farmers' experience and education level did not influence productive efficiencies. Farmers weaning more pigs/sow/year were more efficient. Pure grain feeders were more efficient than those who also fed garbage. The choice of frontier methods did not alter the relationship between efficiency measures and various farm-specific factors.

Given current output levels, large farms (> 75 sows) would save 25–40% and medium (25–75 sows) and small farms (< 25 sows) would save up to 50% of their total economic cost if they achieved full efficiency. Overall, large farmers should reduce feed costs and medium and small farmers should reduce labor costs to become more efficient. If current resources were used at full efficiency, large farms could increase their output by 25%, medium farms by 100%, and small farms by about 50%, resulting in an increase in the industry's output large enough to replace the imports of live hogs from the Mainland. These cost savings or additional returns from increased output at full efficiency would increase the industry's net earnings by $6–7 million per year. Despite several problems confronting Hawaii's swine industry, the study indicates considerable potential for improving its performance by increasing productive efficiency.

1. Introduction

The continuous decline of Hawaii's swine industry due to high production costs and low profitability, limited land availability, and increased environmental problems has raised serious concern about its long-term survival. Sharma et al. (1996) and Sharma (1996) have discussed in detail the status of the swine industry in Hawaii. Based on a costs-and-returns survey of 60 swine farms, profitability of various types of swine operations in Hawaii was examined (Sharma et al. 1996). Cost and profitability measures showed substantial variation among the producers surveyed in terms of farm size and other criteria. On average, large farmers had higher profitability compared to medium and small farmers. In fact, many medium and small farms had a negative net return from swine production. Improving profitability through more efficient utilization of available resources is key to the survival of these swine farms. These issues can be better explained in terms of relative productive efficiency, returns to scale, and economies of size.

Productive efficiency can be determined by estimating the "best-practice" production frontier, and the discrepancy between the frontier and individual producers gives a measure of inefficiency. A producer may be inefficient for several reasons. Failing to achieve maximum output from a given level of inputs (technical inefficiency), using inputs in wrong proportions given their prices (allocative inefficiency), and failing to achieve the optimum scale of operation (scale inefficiency) are the major sources of inefficiency. The product of technical and allocative efficiencies yields economic efficiency. Inefficiency increases cost and *ceteris paribus,* reduces profit. Identification of inefficient producers and of sources of inefficiency are key to promoting efficient utilization of resources and hence to enhancing profitability.

Since Farrell's (1957) pioneering work, several techniques have been developed for efficiency analysis using production frontiers. Among several other economists, Coelli (1995) provides an excellent review of these developments in frontier modeling and efficiency measurement including applications of frontier methods in agriculture. Among them, stochastic production frontier and data envelopment analysis (DEA) are the most popular. The main strength of the stochastic frontier approach is that it can deal with stochastic noise. The need for imposing an explicit functional form for the underlying technology and an explicit distributional assumption for the inefficiency term is the main weakness of the stochastic approach. The main advantage of the DEA approach is that no explicit functional form needs to be imposed on the data, and DEA can easily accommodate multiple outputs. However, since DEA is deterministic and attributes all the deviations from the frontier to inefficiencies, a frontier estimated by DEA is likely to be sensitive to measurement errors or other statistical noise in the data. Because of the different strengths and weaknesses of the two techniques, both the stochastic and DEA frontiers were estimated to examine various production efficiencies of Hawaii swine producers.

In view of growing competition and high production costs, productive efficiency and profitability will become increasingly important determinants of the future of Hawaii's swine industry. In addition to developing and adopting new production technologies, the industry can maintain its economic viability by improving the efficiency of existing operations with a given technology. In other words, the industry's total cost can be reduced and industry's total output can be increased by making better use of available inputs and technology. The maintenance of relative profitability vis-à-vis other producers depends on the maintenance of relative efficiency and the amount of resources inefficiently used. This study examined the farm as well as industry level efficiency so as to identify the sources where improvements can be made. The study will provide vital information to help individual producers in using their resources more efficiently and to assist the industry in becoming more competitive and maintaining its long-term survival.

The determination of frontier technology and knowledge of productive efficiency and its relationship with farm size can provide important insights into the future of Hawaii's swine industry. Furthermore, the relationship between efficiency levels and various farm-specific factors can provide useful policy-relevant information. A comparison of the industry's frontier or "best practice" function and its "average practice" function will produce useful information about possible future structural adjustments for the industry.

2. Research objectives

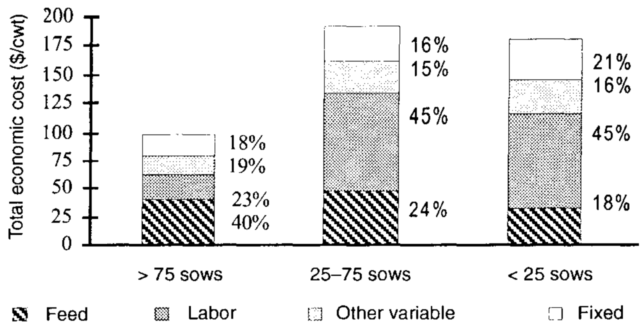
Despite the importance of productive efficiency for individual producers as well as the whole industry, there has been a lack of such information for Hawaii's swine industry. The general objective of this study was to examine productive efficiency for swine producers in

Table 1. Study population and sample of swine producers by farm size.

Farm size	Population		Sample		Sample Population (%)
	No.[a]	% of farms	No.	% of farms	
> 75 sows	21	8.8	19	31.7	90.5
25–75 sows	35	14.7	20	33.3	57.1
< 25 sows	182[b]	76.5	21	35.0	11.5
Total	238	100.0	60	100.0	25.2

[a]The number includes only farms with known number of sows.
[b]Of these, 106 farms had fewer than 10 sows.

Figure 1. Contribution of feed, labor, other variable, and fixed inputs to total economic cost.



Hawaii and to suggest ways to improve producers' and hence the industry's performance. The specific objectives of the study were to:

1) estimate the frontier or "best practice" production function of Hawaii's swine industry using the stochastic production frontier approach and data envelopment analysis (DEA) approach and compare the results obtained from the two techniques;
2) identify the sources of inefficiency by calculating the economic, technical, allocative, and scale efficiencies for individual producers;
3) determine factors affecting efficiency by examining the relationship between efficiency levels and various farm-specific factors; and
4) examine the industry's potential for reducing costs and increasing production at full efficiency.

3. Data

This study is based on a costs-and-returns survey of 60 swine farms carried out during the fall of 1994. Survey procedures, characteristics of farms surveyed, and analysis of costs and returns have been discussed in detail in previous studies (Sharma et al. 1996, and Sharma 1996). Table 1 shows the study population and sample of swine producers by farm size.

3.1. Output and input variables for efficiency analysis

3.1.1. Output variable

In swine production, output produced can be categorized into primary product and secondary product. The primary product includes the production of market hogs, roasters, feeder pigs, suckling pigs, and breeding animals. The secondary product consists of culled breeding stock. The output produced can be measured in terms of physical quantity (i.e., total live weight of pigs sold) or in terms of monetary value (i.e., total returns). Because the share of culled breeding stock in total returns is quite small, the quantity of primary output produced (i.e., total live weight of market hogs, roasters, feeder pigs, suckling pigs, and breeding stock sold) is used as the output variable in efficiency analysis. Because the primary product consists of different products with different prices, the output produced is normalized so as to make it homogenous across farms. Output normalization is explained in Appendix A-1.

3.1.2. Input variables

Swine production is characterized by multiple inputs. For efficiency analysis, inputs have been categorized into four categories: feed, labor, other variable inputs, and fixed inputs. Figure 1 shows the contribution of each of these inputs to total economic cost by farm size. Feed is the dominant component (40%) in the total economic cost on large farms (> 75 sows) and labor is dominant (45%) on medium and small farms (≤ 75 sows).

Feed: Feed is one of the main variable inputs in swine production. Feed expenses include the cost of different types of grain-based feeds and the cost of other feed materials, especially garbage. Because the actual cash expenses for garbage are insignificant relative to total feed costs, and the quantity of garbage fed is difficult to estimate, the quantity of all grain-based feeds is used as a measure of feed input in efficiency analysis. This may underestimate total feed quantity among garbage feeders. However, because garbage feeding uses more labor, the quantity of garbage fed will be reflected by high labor input among garbage feeders. The feed price is the weighted average price for different types of grain-based feeds.

Labor: Labor includes both family and hired labor used in swine production and is measured in total person-days, assuming eight hours per day. The wage is computed as the weighted average of the opportunity wage of family labor, assumed to be $6.94/hour (Hawaii Agricultural Labor 1994), and the actual wage paid for the hired labor, which varied from $3.85/hour to $19.70/hour with an average of $9.30/hour.

Other variable inputs: All the variable inputs except feed and hired labor are included under other variable inputs. These include veterinary and breeding costs, utilities, fuel and gas, repairs and maintenance, and other miscellaneous items. These are measured in dollar value. In view of lack of information on short-term interest rates on operating expenses, the price of other variable inputs is approximated by the average interest rate paid by the swine producers for borrowed capital during the last five years (9.1% per annum).

Fixed inputs: Fixed inputs include fixed cash costs (property taxes, insurance, interest payments, and lease), depreciation, and cost of owner capital. These are also measured in dollar value. The price of fixed inputs is estimated at 7.8% per annum (the average interest rate on borrowed capital).

4. Methodology

Technical, allocative, and economic efficiency scores were derived by estimating the stochastic production frontier, and pure technical, scale, and overall technical efficiency scores were computed by solving constant returns to scale (CRS) and variable returns to scale (VRS) input-oriented and output-oriented DEA models.

The technical efficiency score indicates the producer's ability to achieve maximum output from given quantities of inputs or to use the least quantities of inputs given the level of output. Allocative efficiency measures the producer's ability to use inputs in correct proportions given their prices and to achieve minimum costs given the level of output. Economic efficiency is the product of technical and allocative efficiencies. In DEA, the input-oriented technical efficiency score measures the ability to use minimum input quantities given the level of output and the output-oriented score measures the ability to produce maximum output from given quantities of inputs. Technical efficiency obtained from CRS DEA models is called overall technical efficiency (both technical and scale efficiencies) and that from VRS DEA models is called pure technical efficiency (technical efficiency only). The ratio of overall technical efficiency to pure technical efficiency yields scale efficiency. The mathematical details are explained for the stochastic production frontier in Appendix A-2 and for the DEA models in Appendix A-3. The corresponding models and estimation procedures are presented in Appendices A-4 and A-5, respectively. Factors affecting the efficiency scores were determined by examining the relationships between efficiency scores and various farm-specific factors, such as farm size, operator's education level and experience, number of pigs weaned per sow per year, feed type (grain and garbage feeders), and location (Oahu and Neighbor Islands). The role of full efficiency in farm profitability and the industry's potential for reducing costs and raising production was also examined.

5. Results and discussion

5.1. Technical, allocative, and economic efficiency from the stochastic production frontier

Of the 60 farms surveyed, 53 were used in efficiency analysis (7 were excluded due to incomplete data). As shown in Table 2, the average technical (TE), allocative (AE), and economic efficiency (EE) scores for Hawaii swine producers based on the stochastic production frontier were 70.4, 76.0, and 53.1%, respectively. The majority of farms fell within the 70–80%, 80--90%, and 50–60% ranges of technical efficiency, allocative efficiency, and economic efficiency, respectively. The efficiency estimates for Hawaii's swine producers could not be compared with other studies because, to our knowledge, no such estimates for swine farms have been reported in the efficiency literature.

5.1.1. Factors affecting technical, allocative, and economic efficiency

The relationship between efficiency measures and various farm-specific factors was examined using the ANOVA procedure. The factors analyzed were (a) farm size measured in terms of the number of sows; (b) education level of the farm operator; (c) experience, measured in terms of the number of years of the operator's farm existence; (d) herd performance, measured in terms of number of pigs weaned per sow per year; (e) feed type; and (f) location of the farm. These results are presented in Table 3.

Table 2. Frequency distributions of technical (TE), allocative (AE), and economic efficiencies (EE) from stochastic production frontier.

Efficiency level (%)	TE	AE	EE
< 40	1[a]	0	8
40–50	4	2	14
50–60	3	6	18
60–70	12	10	8
70–80	23	8	5
80–90	10	21	0
90–100	0	6	0
100	0	0	0
Total farms	53	53	53
Mean	70.4	76.0	53.1
Minimum	30.8	45.4	27.1
Maximum	88.7	95.4	77.8
Standard deviation	12.4	12.5	11.9

[a]Denotes the number of farms.

Table 3. Average (%) technical (TE), allocative (AE), and economic (EE) efficiencies and farm-specific factors.

Factor	N	TE	AE	EE
Farm size				
< 25 sows	13	72.2	66.8	47.1
25–75 sows	19	64.1	76.4	48.5
> 75 sows	19	75.4	81.8	61.7
F-statistic		4.49**	6.61***	10.9***
Education				
Below high school	13	72.1	74.6	53.6
High school	27	70.3	74.5	51.9
College	13	69.1	80.6	55.1
F-statistic		0.20	1.18	0.33
Experience				
< 10 years	16	66.9	75.8	49.8
≥ 10 < 30 years	19	71.0	75.1	52.9
≥ 30 years	18	72.9	77.3	56.4
F-statistic		1.01	0.15	1.33
Pigs weaned/sow/year				
< 13 pigs	14	64.2	74.0	46.6
≥ 13 < 17 pigs	22	72.9	78.9	57.2
≥ 17 pigs	15	72.6	73.5	53.0
F-statistic		2.45*	1.04	3.66**
Feed type				
Grain	31	71.5	77.7	55.4
Garbage	22	68.9	73.7	49.9
F-statistic		0.56	1.37	2.87*
Island				
Oahu	28	72.4	76.5	55.0
Neighbor Islands	25	68.2	75.5	51.0
F-statistic		1.51	0.08	1.54

***Significant at 1%, **significant at 5%, and *significant at 10%.
N denotes the number of farms. Total number of farms under farm size and pigs weaned/sow/year is 51 instead of 53 because two farms that bought feeder pigs from others and had no sows are excluded in the ANOVA.

Overall, farm size had a significant effect on efficiency estimates. However, the relationship between farm size and technical efficiency was rather ambiguous in that efficiency was similar for farms with more than 75 sows and for those with fewer than 25 sows. However, farm size was positively and significantly associated with allocative and economic efficiencies. For example, farms with 25 or more sows were significantly more allocatively efficient than those with fewer than 25 sows. In terms of economic efficiency, farms with more than 75 sows were more efficient than those with 75 or fewer sows.

Education level and experience of the farm operator did not show a significant association with any of the efficiency measures. The relation between herd performance and efficiency was mixed. In terms of economic efficiency, grain feeders seemed more efficient than garbage feeders. Farmers on Oahu and those on Neighbor Islands were equally efficient.

5.1.2. Industry cost savings at full efficiency from stochastic production frontier

Based on the estimates of various efficiency measures discussed in the previous section, the industry's total economic costs that can be saved if all producers operate at full efficiency are also estimated. These results are presented in Table 4.

At full technical and allocative efficiency levels (or full economic efficiency), farms with more than 75 sows will be able to save about 40% and those with less than 75 sows will be able to save 50% of their current total economic cost given the existing levels of production. Most of the cost savings (55–65%) come from improving technical efficiency. About 55% of the cost savings of larger farms come from reducing feed, and 50–54% of the savings of medium and small farms come from reducing labor. All farm sizes have the potential for reducing fixed costs by 27–33%. The observed and technically and economically efficient input vectors are presented in Appendix Table B-1.

Table 4. Cost savings and net return at full efficiency from stochastic production frontier by farm size.

	Farm size			
	> 75 sows	25–75 sows	< 25 sows	All farms
No. of sample farms analyzed	19	19	15	53
Average for sample farms ($1,000)				
Observed total economic cost	320.27	81.03	48.23	157.51
Observed net return	77.46	– 17.20	– 7.93	19.36
Cost saved at full technical efficiency	79.19	29.16	14.04	42.81
Cost saved at full allocative efficiency	44.97	12.48	10.53	23.58
Cost saved at full economic efficiency	124.16	41.65	24.57	66.39
Net return at full economic efficiency	201.62	24.45	16.64	85.75
Total for the whole industry[a] ($1,000)				
Observed total economic cost	6,725.57	2,836.22	3,665.25	13,227.04
Observed net return	1,626.57	– 602.04	– 602.51	422.02
Cost saved at full technical efficiency	1,662.90	1,020.72	1,066.84	3,750.46
Cost saved at full allocative efficiency	944.46	436.87	800.48	2,181.81
Cost saved at full economic efficiency	2,607.36	1,457.59	1,867.32	5,932.27
Net return at full efficiency	4,233.93	855.55	1,264.81	6,354.29
Costs saved by input categories (% of total savings)				
Feed	54.5	20.4	10.2	29.7
Labor	9.8	53.6	50.2	36.9
Other variable inputs	4.2	–1.2*	6.2	2.9
Fixed inputs	31.5	27.1	33.4	30.5

[a]Estimated cost savings for the industry are based on the sample averages and the number of farms listed in Table 1. For farms with less than 25 sows, those with 10-25 sows are used for the industry projection.
*Negative shares in total savings imply that efficient input costs are greater than observed input costs.

If all farmers achieve full efficiency, Hawaii's swine industry can save up to about $6 million of total economic cost annually, thus increasing the industry's net return by the same amount. If medium and small producers can realize some of these savings through improvement in efficiency, they can earn a positive rather than a negative net return from swine production. Large producers can also increase their net return significantly.

The average total economic cost savings at full efficiency for grain and garbage feeders are presented in Table 5. In terms of the percentage of total economic costs saved at full efficiency, there is not much difference between grain and garbage feeders. However, except for medium sized farms, the actual savings are higher for grain than for garbage feeders. Most of the cost savings (60–75%) are due to improvements in technical efficiency, except for small garbage feeders whose cost savings come mainly from improving allocative efficiency. Overall, grain feeders need to reduce feed cost and garbage feeders need to reduce labor cost to be more efficient. In some cases, farmers need to increase the amount of some inputs. For example, medium grain feeders and large garbage feeders need to increase other variable inputs, and small garbage feeders need to increase feed (Table 5 and Appendix Table B-2). It should be noted that because feed includes only grain-based feeds and not the amount of garbage, feed input is generally understated for garbage feeders. High labor cost for garbage feeders is due to the collection of garbage. The improvement in efficiency by reducing feed cost among grain feeders and by reducing labor cost among garbage feeders is limited by the fact that pigs must get some minimum amount of feed, either grain or garbage or both, for their normal growth.

Table 5. Average cost savings and net return at full efficiency from stochastic production frontier for grain feeders vs. garbage feeders.

	Farm size			
	> 75 sows	25–75 sows	< 25 sows	All farms
Grain feeders				
No. of grain feeders analyzed	15	7	9	31
Average for sample grain feeders ($1,000)				
Observed total economic cost	371.24	84.49	55.39	214.79
Observed net return	86.26	− 9.83	− 10.35	36.51
Cost saved at full technical efficiency	92.64	25.94	18.25	55.98
Cost saved at full allocative efficiency	51.99	15.72	9.23	31.39
Cost saved at full economic efficiency	144.63	41.66	27.48	87.37
Net return at full economic efficiency	230.89	31.83	17.13	123.88
Costs saved by input (% of total savings)				
Feed	61.3	45.1	25.8	47.3
Labor	1.1	36.6	24.9	16.0
Other variable inputs	9.1	− 13.2*	14.1	5.5
Fixed inputs	28.5	31.4	35.2	31.1
Garbage feeders				
No. of garbage feeders analyzed	4	12	6	22
Average for sample garbage feeders ($1,000)				
Observed total economic cost	129.10	79.02	37.49	76.80
Observed net return	44.44	− 21.50	− 4.30	− 4.82
Cost saved at full technical efficiency	28.73	31.04	7.73	24.26
Cost saved at full allocative efficiency	18.66	10.60	12.48	12.58
Cost saved at full economic efficiency	47.39	41.64	20.21	36.84
Net return at full economic efficiency	91.83	20.14	15.91	32.02
Costs saved by input (% of total savings)				
Feed	28.9	6.0	− 13.3	4.9
Labor	42.3	63.5	88.2	66.4
Other variable inputs	− 13.9	5.8	− 5.5	− 0.9
Fixed inputs	42.6	24.6	30.6	29.5

*Negative shares in total savings imply that efficient input costs are greater than observed input costs.

5.2. Pure technical, scale, and overall technical efficiency in DEA

DEA models were estimated using IDEAS (Version 5.1). Table 6 shows the pure technical (TE_{VRS}), scale (SE), and overall technical efficiency (TE_{CRS}) estimates for sampled swine producers derived from input-oriented and output-oriented DEA models. The average input-oriented pure technical, scale, and overall technical efficiency scores for the sample swine producers were 74.8, 84.2, and 63.5%, respectively. According to input-oriented results, about one-third of the producers were pure technical and scale efficient and about 20% of the producers were overall efficient.

In terms of output-oriented results, the average pure technical, scale, and overall technical efficiencies were 72.6, 89.5, and 64.3%, respectively, and did not differ from the corresponding estimates in the input-oriented model. In terms of output-orientation, about one-third of the farms were pure technical efficient and less than 20% of the farms were fully efficient in terms of scale and overall technical efficiency measures.

Input-oriented DEA models were also estimated for

Table 6. Frequency distributions of pure technical (TE_{VRS}), scale (SE), and overall technical (TE_{CRS}) efficiencies from input- and output-oriented DEA models.

	Input-oriented DEA			Output-oriented DEA		
Level (%)	TE_{vrs}	SE	TE_{crs}	TE_{vrs}	SE	TE_{crs}
< 40	4[a]	0	9	5	0	8
40–50	3	5	7	5	3	8
50–60	7	4	10	8	0	9
60–70	10	4	7	9	3	8
70–80	5	3	3	3	3	3
80–90	5	8	7	2	9	7
90–100	2	12	0	4	24	0
100	17	17	10	17	11	10
Total farms	53	53	53	53	53	53
Mean	74.8	84.2	63.5	72.6	89.5	64.4
Minimum	25.5	41.3	14.1	14.5	43.1	14.3
Maximum	100	100	100	100	100	100
Standard deviation	21.9	19.5	24.7	25.3	13.9	24.5

[a]Denotes the number of farms.

grain and garbage feeders separately. Overall, grain feeders were significantly more efficient than garbage feeders. The average overall technical efficiency score for grain feeders was 77.0% vs. 59.7% for garbage feeders. However, there was no difference in efficiency between grain feeding and garbage feeding among large farms. The difference in technical efficiency between grain feeders and garbage feeders was the highest for medium sized farms (Table 7).

5.2.1 Factors affecting efficiency in DEA

As in the stochastic frontier, the ANOVA was used to evaluate the relationship between input-oriented and output-oriented efficiency scores and various farm characteristics. These results are presented in Table 8.

Overall, farm size had a significant effect on all three efficiency measures obtained from the two orientations. The relationship between farm size and pure technical efficiency scores was rather ambiguous, as these scores for large farms (> 75 sows) and small farms (< 25 sows) were quite similar and those for medium size farms (25–75 sows) were significantly smaller. Farm size was positively and significantly associated with scale and overall technical efficiency obtained from the two models. In terms of scale efficiency measures, there was some difference between input-oriented and output-oriented models. In the input-oriented case, scale efficiency was higher for large farms compared to medium and small categories, whereas in the output-oriented case this score was higher for large and medium farms compared to smaller ones. Overall, ANOVA results of the stochastic and DEA frontiers were similar.

Education level and experience of the farm operator did not affect any efficiency measures obtained from the two models. The relation between herd performance and efficiency was significant, and farmers weaning more pigs per sow per year seemed to be more efficient in both orientations. In terms of pure technical efficiency, grain feeders tended to be more efficient than garbage feeders. Oahu farmers were more scale efficient than those on Neighbor Islands.

5.2.2. Cost savings at full efficiency from input-oriented DEA

As discussed in Appendix A-3, the input-oriented model seeks to maximize the reduction in inputs for a given output level. The output-oriented model seeks to maximize the increase in output from a given amount of inputs. Input-oriented models generate information on how much cost can be saved to produce at least the

Table 7. Input-oriented overall technical efficiency (TE_{CRS}) for grain feeders and garbage feeders by farm size.

	No. of farms	Input-oriented overall technical efficiency (TE_{CRS}) (%) Mean	Minimum	Maximum	Std. deviation
Grain feeders					
> 75 sows	15	79.5	55.1	100.0	14.4
25–75 sows	7	73.8	46.4	100.0	20.0
< 25 sows	9	75.4	38.7	100.0	23.4
All farms	31	77.0	38.7	100.0	18.2
Garbage feeders					
> 75 sows	4	79.2	38.7	100.0	28.9
25–75 sows	12	49.1	14.1	100.0	26.2
< 25 sows	6	67.8	42.6	100.0	25.6
All farms	22	59.7	14.1	100.0	28.1

Table 8. Average (%) pure technical (TE_{VRS}), scale (SE), and overall technical (TE_{CRS}) efficiencies from DEA and farm-specific factors.

		Input-oriented DEA			Output-oriented DEA		
Factors	N	TE_{VRS}	SE	TE_{CRS}	TE_{VRS}	SE	TE_{CRS}
Farm size							
< 25 sows	13	83.3	71.2	51.4	77.8	80.6	60.5
25–75 sows	19	60.7	82.6	59.5	56.7	91.6	52.2
> 75 sows	19	80.9	95.1	77.1	82.4	94.4	77.8
F-statistic		6.96***	7.43***	6.28***	6.58***	4.73**	6.39***
Education							
Below high school	13	80.7	81.2	65.6	75.3	90.0	66.8
High school	27	71.1	85.2	60.8	70.1	88.4	61.5
College	13	76.7	85.1	67.2	75.2	91.4	68.0
F-statistic		0.91	0.20	0.34	0.26	0.20	0.39
Experience							
< 10 years	16	68.5	82.4	58.4	65.6	90.5	59.1
≥ 10 < 30 years	19	75.0	83.7	62.8	72.9	88.4	64.0
≥ 30 years	18	80.2	86.4	68.8	78.6	89.8	69.4
F-statistic		1.22	0.18	0.75	1.12	0.10	0.75
Pigs weaned/sow/year							
< 13 pigs	14	64.8	70.2	44.6	57.7	82.8	44.9
≥ 13 < 17 pigs	22	74.1	92.3	69.3	73.5	94.6	70.0
≥ 17 pigs	15	82.3	85.9	71.1	82.1	89.4	72.4
F-statistic		2.49*	6.77***	6.40***	3.84**	3.48**	7.10***
Feed type							
Grain	31	79.3	85.9	67.9	78.1	89.3	68.8
Garbage	22	68.5	81.8	57.4	64.9	89.7	58.2
F-statistic		3.28*	0.55	2.37	3.69*	0.01	2.50
Island							
Oahu	28	74.5	91.0	68.9	73.1	94.4	69.6
Neighbor islands	25	75.2	76.6	57.5	72.1	84.1	58.7
F-statistic		0.01	8.26**	2.93*	0.02	8.20**	2.76

*** Significant at 1%, ** significant at 5%, and *significant at 10%.
N denotes the number of observations in each category. Total number of farms under farm size and pigs weaned/sow/year is 51 instead of 53 because two farms that bought feeder pigs from others and had no sows are excluded in the ANOVA.

Table 9. Cost savings at full efficiency level from input-oriented DEA by farm size.

	Farm size			
	> 75 sows	25–75 sows	< 25 sows	All farms
Average for sample farms ($1,000)				
Observed total economic cost	320.27	81.03	48.23	157.51
Observed net return	77.46	– 17.20	– 7.93	19.36
Cost saved by pure technical efficiency	57.52	36.86	15.02	38.09
Cost saved by scale efficiency	26.51	5.48	8.10	13.76
Cost saved by overall efficiency	84.03	42.34	23.12	51.85
Net return at full efficiency	161.49	25.14	15.19	71.21
Total for the industry[a] ($1,000)				
Observed total economic cost	6,725.57	2,836.22	3,665.25	13,227.04
Observed net return	1,626.57	– 602.04	– 602.51	422.02
Cost saved by pure technical efficiency	1,208.01	1,289.96	1,142.03	3,640.01
Cost saved by scale efficiency	556.70	191.88	615.44	1,364.02
Cost saved by overall efficiency	1,764.71	1,481.84	1,757.47	5,004.03
Net return at full efficiency	3,391.28	879.80	1,154.96	5,426.05
Costs saved by input categories (% of total savings)				
Feed	41.8	25.7	17.2	34.0
Labor	16.2	42.3	25.6	25.1
Other variable inputs	13.9	13.5	35.9	16.5
Fixed inputs	28.1	18.4	21.2	24.5

[a]Estimated based on the sample averages and the number of farms listed in Table 1. For farms with less than 25 sows, only those farms with 10-25 sows were used for estimating total cost savings for the industry.

existing output level, and output-oriented models generate information on how much additional output can be produced from no more than the existing resources if everyone operates at the efficient frontiers.

Based on input-oriented results, Table 9 presents the average cost savings for the sample producers and the total cost savings for the industry if all farms operate at full efficiency. If operated at full technical and scale efficiency levels, large farms will be able to save about 25% and medium and small farmers will be able to save nearly 50% of their current total economic cost. Most of these savings (about 65–85%) come from increasing technical efficiency. The total annual industry cost savings of about $5 million will be equally distributed across different farm categories. By input types, most of the cost savings for large farms come from reducing the amount of feed (42%), followed by fixed costs (28%). For medium farms, most savings come from reducing labor (42%), followed by feed (26%). For smaller farms, the reduction in other variable costs, labor, and fixed costs results in cost savings. These results are quite comparable with results obtained from the stochastic production frontier. These cost savings will have a significant and positive impact on the profitability of swine production in Hawaii.

The average full input-efficiency cost savings for grain and garbage feeders are presented in Appendix Table B-3. Among grain feeders, large, medium, and small farmers will be able to save 26.4, 44.4, and 42% of their current total economic cost. The corresponding figures for garbage feeders are 28, 56.6, and 37.6%, respectively. Most of the savings of large grain feeders come from reducing feed cost (40.6%), and those of small grain feeders come from reducing other variable costs (51%). Feed accounted for more than half of the total costs savings for large garbage feeders, while labor contributed to most of the cost savings for medium and small garbage feeders (44–53%).

Input-specific efficiency scores are also computed for inefficient units relative to inputs used by efficient

Table 10. Output augmentation at full efficiency from output-oriented DEA by farm size.

		Farm size			
		> 75 sows	25–75 sows	< 25 sows	All Farms
Average for sample farms (1,000 lb live)					
Output	(1,000 lb live)				
Observed output		348.25	55.79	35.85	154.99
Increased output by technical efficiency		54.75	45.67	12.40	39.50
Increased output by scale efficiency		31.60	8.72	7.03	16.44
Increased output by overall efficiency		86.35	54.38	19.43	55.95
Potential output at full efficiency		434.60	110.17	55.28	210.94
Net return and cost savings	($1,000)				
Observed net return		77.46	– 17.20	– 7.93	19.36
Increased return at full efficiency		88.85	58.84	23.16	61.21
Cost saved at full efficiency		24.86	5.66	10.20	13.83
Net return at full efficiency		191.17	47.30	25.43	94.40
Total for the industry[a]					
Output	(1,000 lb live)				
Observed output		7,313.16	1,952.58	2,724.83	11,990.56
Increased output by technical efficiency		1,149.83	1,598.36	942.23	3,690.42
Increased output by scale efficiency		663.57	305.09	534.12	1,502.79
Increased output by overall efficiency		1,813.40	1,903.45	1,476.36	5,193.21
Potential output at full efficiency		9,126.56	3,856.03	4,201.18	17,183.77
Net return and cost savings	($1,000)				
Observed net return		1,626.57	– 602.04	– 602.51	422.02
Increased return at full efficiency		1,865.99	2,059.53	1,759.82	5,685.34
Cost saved at full efficiency		522.03	198.03	775.06	1,495.12
Net return at full efficiency		4,014.59	1,655.52	1,932.37	7,602.48

[a]Estimated based on the sample averages and the number of farms listed in Table 1. For farms with less than 25 sows, only those farms with 10–25 sows were used for estimating increased output and cost savings for the industry.

units in the sample. These results are presented in Appendix Table B-4. Among all inefficient producers, large producers are most efficient in using all four input categories. Interestingly, relative to efficient farms, small farms are more efficient in using inputs than medium ones, except for fixed inputs. Input-specific efficiency scores are also computed for inefficient grain feeders (Appendix Table B-5) and inefficient garbage feeders (Appendix Table B-6) relative to their efficient counterparts. Among grain feeders, large farms are more efficient than small and medium farms. Comparing medium and small grain feeders, medium ones are relatively more efficient than small ones in using feed, other variable inputs, and fixed inputs, whereas small ones are more efficient in using labor. Among inefficient garbage feeders, small farms are most efficient in using feed, large farms are most efficient in using labor, and medium farms are least efficient in using all inputs except fixed inputs. Again, it should be noted that feed input is understated for garbage feeders because the amount of garbage fed is not included as feed input.

5.2.3. Output augmentation at full efficiency from output-oriented DEA

Based on output-oriented results, Table 10 presents the potential output increase for the sample producers and for the whole industry if everybody operates on the efficient frontier. Results show that large farms could increase their output by about 25%, medium farms by nearly 100%, and smaller farms by more than 50% if they all operate on the frontier. Most of the output increase comes from increasing technical efficiency (63% for larger farms, 84% for medium farms, and 64% for smaller farms). In addition to increased output, the producers could also realize substantial cost savings if they operate on the output-oriented frontier. It is interesting to note that the input-oriented model did not show much increase in output. Only three farms had some output slacks in the input-oriented analysis.

When these results are projected for the whole industry, the total annual live hog production in Hawaii increases by more than 5 million pounds, which is equivalent to about 23,000 live market hogs (assuming 225 lb/hog). That means Hawaii can become more than self-sufficient in terms of the demand for hot pork, thus eliminating the imports of live hogs from the U.S. Mainland. Of the total incremental production for the industry, 35% will come from larger farms, 37% from medium farms, and 28% from smaller farms. In addition, the industry can save up to $1.5 million in total economic costs if all farms operate on the output-oriented frontier.

5.3 DEA vs. stochastic production frontier

DEA and the stochastic frontier were compared only in terms of technical efficiency (Table 11). Given the methodology used in the stochastic frontier, it is appropriate to compare stochastic technical efficiency with input-oriented technical efficiency measures in DEA. On average, the CRS DEA frontier produced a lower ($p = 0.036$) technical efficiency score compared to the technical efficiency score from the stochastic production frontier. Pure technical efficiency (TE_{VRS}) in DEA was more comparable to the technical efficiency in the stochastic frontier. The DEA technical efficiency measures showed a significantly higher ($p = 0.000$) variability than the stochastic measure. The correlation coefficient between technical efficiency from the stochastic frontier (TE) and overall technical efficiency from DEA (TE_{CRS}) was 0.88 ($p = 0.000$) and the corresponding coefficient between TE and TE_{VRS} was 0.75 ($p = 0.000$).

While the stochastic frontier showed constant returns to scale, the VRS measures of technical efficiency (TE_{VRS}) were significantly higher than the corresponding CRS (TE_{CRS}) measures in both input-oriented ($p = 0.007$) output-oriented ($p = 0.045$) DEA models, suggesting the existence of scale inefficiency and variable returns to scale in DEA. The majority of large farms showed decreasing returns to scale, and most of the small farms showed increasing returns to scale in both orientations. The majority of the medium-sized farms showed increasing returns in input-orientation and decreasing regurns to scale in output-orientation (Table 12).

Table 11. Stochastic production frontier vs. input-oriented DEA model.

	Stochastic frontier	Input-oriented DEA[b]	
Level (%)	TE[a]	TE_{VRS}	TE_{CRS}
< 40	1[c]	4	9
40–50	4	3	7
50–60	3	7	10
60–70	12	10	7
70–80	23	5	3
80–90	10	5	7
90–100	0	2	0
100	0	17	10
Mean	70.4	74.8	63.5
Minimum	30.8	25.5	14.1
Maximum	88.7	100	100
Standard deviation	12.4	21.9	24.7

[a]TE stands for technical efficiency from the stochastic frontier.
[b]In DEA, TE_{VRS} denotes pure technical efficiency and TE_{CRS} denotes overall technical efficiency.
[c]Denotes the number of farms.

6. Study limitations

One should look at efficiency estimates for the sample swine producers and implications for the industry in view of some limitations of the study such as sample size, data problems, and methodology used.

Of the total of 350 swine farms in Hawaii, efficiency results are based on data collected from 53 farms. We were not able to include all 350 farms due to the following reasons. First, there was not a complete list of farmers with their complete mailing addresses, so many farmers could not be located. Second, several farmers declined to participate in the survey. Third, the major focus in selecting the sample was given to commercial production. About one-third of the farms in Hawaii are small (< 10 sows), and these farmers were not interviewed, assuming they were not commercial producers. For the same reason, farms with fewer than 10 sows were not included in projections of increased industry output and reduced industry costs that would result from increased efficiency.

Because of small sample size, some potentially interesting and useful analyses could not be carried out. For example, instead of estimating a single production frontier for all observations, it would be interesting to estimate separate efficient frontiers, especially under the

Table 12. Returns to scale in DEA models.

Farm size	Input-oriented			Output-oriented		
	CRS	IRS	DRS	CRS	IRS	DRS
> 75 sows (N = 19)	7	3	9	5	1	13
25–75 sows (N = 19)	3	14	2	2	7	10
< 25 sows (N = 15)	3	12	0	3	12	0
Total farms (N = 53)	13	29	11	10	20	23

Note: Returns to scale is determined by estimating technical efficiency under nonincreasing returns (TE_{NIRS}). Increasing returns to scale (IRS) prevails if $TE_{VRS} > TE_{NIRS}$, and decreasing returns to scale (DRS) prevails if $TE_{VRS} = TE_{NIRS}$. Constant returns to scale (CRS) prevails if $TE_{VRS} = TE_{CRS}$. Returns to scale were determined using DEAP 2.0 (Coelli 1996). N = number of farms.

stochastic approach, for each of the different categories of producers, such as different farm sizes, grain and garbage feeders, finishers and feeder pig producers, and Oahu and Neighbor Islands to examine differences in efficiency measures across different categories. Efficiency measures were derived separately for grain and garbage feeders using DEA.

In addition to those limitations discussed in Sharma et al.(1996), some other data limitations need to be noted. Because of the cross-sectional nature of the data, there was not enough variation in input and output prices, eliminating the possibility of estimating less restrictive cost or profit frontiers instead of production frontiers. Two of the input categories, namely other variable inputs and fixed inputs, were measured in dollar terms. Their prices were approximated by interest rates that may not be their real prices. Because of the lack of information on the amount of garbage fed and a high degree of heterogeneity in garbage, the amount of garbage fed could not be included in feed input. Consequently, feed input was certainly understated for garbage feeders, thus affecting their efficiency scores depending upon the amount of garbage fed relative to grain-based feeds.

The methodology adopted to estimate technical, allocative, and economic efficiencies in the stochastic frontier required a self-dual (such as Cobb-Douglas) functional form for the production function. Thus, the possibility of examining the effects of the choice of different functional forms (such as translog) on efficiency estimates was eliminated. In addition, the efficiency scores estimated from standard input-oriented and output-oriented DEA models may be sensitive to the units of measurement of input and output variables. Despite these limitations, we believe the efficiency results are of significance to Hawaii's swine industry.

7. Conclusions

This study examined the potential of Hawaii's swine industry for improving performance and future expansion based on various productive efficiencies. Despite many problems confronting the industry, the results showed that there is substantial potential for improving productive efficiency. Results also revealed potential for increasing local swine production significantly if existing resources were used more efficiently.

Although profitability results showed a discouraging picture for the industry, with most of the sample farms, especially medium and small farms, earning a negative net return, efficiency results showed substantial potential for reducing production costs and thus earning a positive net return. How the producers can become more efficient is another question, but if they all operate at full efficiency levels, the industry either can increase its output significantly without additional resources or can reduce its production costs significantly given the current level of output. Results showed that the industry could increase its earnings by $6–7 million annually in increased revenues and reduced production costs if farmers operate at full efficiency. With increased production by operating on the efficient frontier, Hawaii can become more than self-sufficient for the demand for hot pork, eliminating the imports of live hogs from the U.S. Mainland. However, the industry will not be able to fully exploit the potential for improving its performance unless the problems facing the producers, especially limited land availability and increasing environmental concerns are eased.

Overall, Hawaii's swine producers are operating at about 55–60% efficiency levels. The study has also generated individual farm-specific information on efficient input and output levels. Inefficient farms can become more efficient either by increasing output using the existing resources or by reducing costs given the current levels of production. Because a lot of farmers have underutilized resources, especially family labor and fixed inputs (housing, capital, and equipment) and since local production does not meet the demand for hot pork, it will be more reasonable to increase production by using existing resources more efficiently.

With respect to future research, there is little opportunity for further study with the current data set. One possibility would be to increase sample size and do some detailed analysis by farm size and other criteria as indicated earlier. This kind of "snapshot" study indicates very little about the industry's technical and structural change over time. Similar studies every 3–4 years will be useful to address these issues.

The amount of garbage fed needs further research. Research on the nutritional composition of garbage is needed to express garbage in grain equivalents. Separate information on labor, fuel, and equipment involved in garbage feeding is important to estimate the price for garbage.

Appendix A-1. Output normalization for efficiency analysis.

Production of different types of pigs is normalized as follows:

$$y_j = \frac{\sum_{r=1}^{s} P_{rj} Q_{rj}}{\left(\sum_{j=1}^{n} \overline{P}_j / N\right)} \qquad (1)$$

where, y_j is the normalized output for the j^{th} farm, s denotes the number of differentiated products, P_{rj} denotes the price of r^{th} product for the j^{th} farm, Q_{rj} denotes the amount of r^{th} product for j^{th} farm,

$$\overline{P}_j = \sum_{r=1}^{s} P_{rj} \cdot Q_{rj} / Q_j, \quad Q_j = \sum_{r=1}^{s} Q_{rj}$$

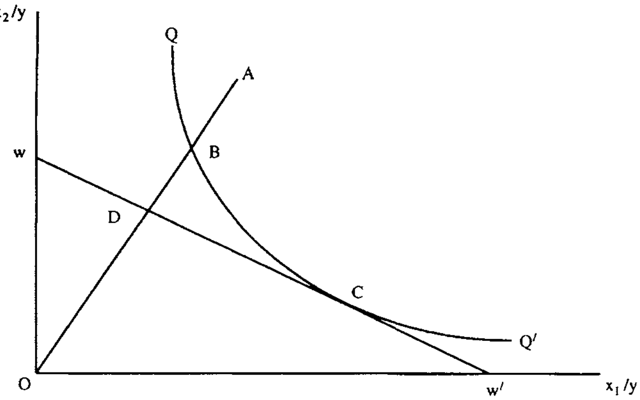
and N denotes the number of farms in the sample. Alternatively, $\overline{P}_j$ is the weighted average price for different types of pigs produced by the j^{th} farm. Thus, the denominator in Eq. (1) is the average pig price received by the swine producers in the sample.

Appendix A-2. Farrell's technical, allocative, and economic efficiency measures

Consider a firm producing output y from inputs x_1 and x_2 with the production function (frontier) $y = f(x_1, x_2)$. Assuming constant returns to scale, the frontier technology can be represented by the unit isoquant, $1 = f(x_1/y, x_2/y)$, QQ′ (Appendix Figure A-1). Let ww′ represent the ratio of input prices. Farrell defines a firm producing at point A as technically inefficient and the ratio OB/OA gives Farrell's measure of technical efficiency. Point B is technically efficient but allocatively inefficient and the ratio OD/OB is Farrell's measure of allocative efficiency. Finally, the ratio OD/OA measures total efficiency. Note that total efficiency is equal to the product of technical and allocative efficiencies.

Using neoclassical duality theory, Kopp and Diewert (1982) have used a cost function approach to deriving Farrell's measures of technical, allocative, and overall economic efficiencies. Assuming QQ′ in Appendix Figure 1 as the efficient isoquant associated with a certain level of output, and the equation of line ww′ is $\{\mathbf{x}: \mathbf{w}'\mathbf{x} = \mathbf{w}'\mathbf{x}^C\}$, Kopp and Diewert define technical efficiency as the ratio of total cost at point B to total cost at point A, $\mathbf{w}'\mathbf{x}^B/\mathbf{w}'\mathbf{x}^A$, allocative efficiency as the ratio of total cost

Appendix Figure A-1. Farrell's technical, allocative, and economic efficiency measures.



Appendix Table A-1. Technical, allocative and economic efficiency.

Efficiency measure	Farrell (1957)	Kopp and Diewert (1982)
Technical efficiency	OB/OA	$\mathbf{w'x^B / w'x^A}$
Allocative efficiency	OD/OB	$\mathbf{w'x^C / w'x^B}$
Economic efficiency	OD/OA	$\mathbf{w'x^C / w'x^A}$

at D to total cost at B, $\mathbf{w'x^C/w'x^B}$, and overall economic efficiency as the ratio of the total cost at D to the total cost at A, $\mathbf{w'x^C/w'x^A}$, where $\mathbf{w}$ is the price vector and $\mathbf{x}$ the input vector. A firm may fail to produce an output at minimum cost due to the presence of technical inefficiency or allocative inefficiency or both. These efficiency measures are summarized in Appendix Table A-1.

This study follows the Kopp and Diewert approach to estimating technical, allocative, and economic efficiencies for Hawaii swine producers. Bravo-Ureta and Rieger (1991) and Bravo-Ureta and Evenson (1994) have also used the Kopp and Diewert approach. This approach is presented below.

The technology is represented by a frontier production function as:

$$y = f(\mathbf{x}_a, \beta) \tag{2}$$

where y is output, $\mathbf{x}_a$ is a vector of input quantities, and β is a vector of parameters to be estimated. The technically efficient input vector, $\mathbf{x}_t$, for a given level of production ($\tilde{y}$) is derived by solving simultaneously equation (2) and the input ratios $x_1/x_i = k_i$ $(i > 1)$, where k_i is the ratio of observed inputs x_1 and x_i at output $\tilde{y}$. Assuming that the production function is self-dual (e.g., Cobb-Douglas), then the corresponding cost function associated with output y and input price vector $\mathbf{w}$ can be derived analytically as:

$$C = C(\mathbf{w}, y, \theta) \tag{3}$$

where θ is a vector of parameters. The economically efficient input vector, $\mathbf{x}_e$, is derived by applying Shephard's lemma and substituting the firm's input prices and output level into the resulting system of input demand equations as:

$$\frac{\partial C}{\partial w_i} = x_i(w, y; \psi) \tag{4}$$

where ψ is a vector of parameters. Then technical (TE), allocative (AE), and overall economic (EE) efficiency indices can be computed as:

$$TE = \mathbf{x}'_t\mathbf{w}/\mathbf{x}'_a\mathbf{w} \tag{5}$$

$$AE = \mathbf{x}'_e\mathbf{w}/\mathbf{x}'_t\mathbf{w} \tag{6}$$

$$EE = \mathbf{x}'_e\mathbf{w}/\mathbf{x}'_a\mathbf{w} \tag{7}$$

Appendix A-3. Pure technical, scale, and overall technical efficiencies in DEA models

Farrell's original nonparametric approach, now known as data envelopment analysis (DEA), to measuring technical efficiency of each decision making unit (DMU) was generalized to a linear programming (LP) problem by Charnes, Cooper, and Rhodes (CCR) (1978). The essential characteristic of the DEA model is the reduction of the multiple-output multiple-input situation for each DMU to that of a single "virtual" output and "virtual" input. The ratio of this single virtual output to single virtual input of each DMU provides the measure of efficiency.

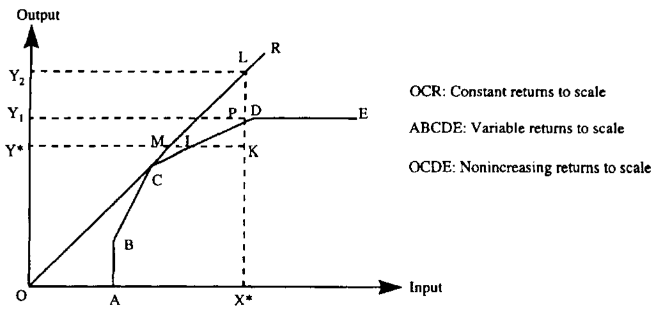
The basic CCR models embody constant returns to scale (CRS). Variable returns to scale (VRS) DEA models were developed by Banker et al. (1984). Constant returns to scale, variable returns to scale, and non-increasing returns to scale are illustrated in Appendix Figure A-2. Under CRS, any DMUs lying on the ray, OCR, are efficient and those lying below it are inefficient. Because variable returns to scale allows both increasing and decreasing returns, the VRS frontier may include scale-inefficient DMUs that may be technical efficient for a given scale, resulting in the piecewise linear frontier ABCDE in Appendix Figure A-2.

In general, the CRS efficiency comparison gives a poorer performance because a DMU has to be both technical and scale efficient to be efficient. Under VRS technology, dominance is weaker in the sense that scale-inefficient production may qualify as a "best practice" if it is technical efficient. VRS efficiency is also known as pure technical efficiency to distinguish it from CRS efficiency, which involves both technical and scale components in performance. For DMU "K" in Appendix Figure A-2, it can easily be seen that technical efficiency under constant returns to scale is equal to or less than that under variable returns to scale, i.e., $TE_{K,CRS} \leq TE_{K,VRS}$. This relationship is used to estimate the scale efficiency for the k[th] DMU as $SE_K = TE_{K,CRS}/TE_{K,VRS}$. Scale inefficiency is due to increasing or decreasing returns to scale, which can be determined by comparing the VRS technical efficiency score with that estimated under nonincreasing returns to scale (NIRS).

The input-oriented and output-oriented technical efficiency scores under constant returns to scale (TE_{CRS}) and variable returns to scale (TE_{VRS}), and resultant scale efficiency (SE) of the k[th] DMU can easily be derived from Appendix Figure A-2 and are presented in Appendix Table A-2.

An inefficient firm can reach the frontier by reducing its inputs (input-orientation) or by augmenting its outputs (output-orientation). The input reduction/output augmentation is achieved at two stages. Input-oriented models yield input-oriented projections and output-oriented models yields output-oriented projections. The input-oriented models seek to maximize the proportional decrease in all inputs until one of the input excesses is reduced to zero. The maximal proportional decrease is achieved in the first-stage problem. The resulting intermediate point is employed in the second-stage problem to obtain the projected point. Output-oriented models maximize the proportional increase in the output vector while remaining within the envelopment surface. A proportional increase in all outputs is possible until at least one of the output slacks is reduced to zero.

Appendix Figure A-2. Returns to scale in DEA.



Appendix Table A-2. Efficiency for input-oriented and output-oriented DEA surfaces.

Efficiency	Input-oriented surface	Output-oriented surface
Overall technical efficiency (TE_{crs})	Y*M/Y*K	X*K/X*L
Pure technical efficiency (TE_{vrs})	Y*I/Y*K	X*K/X*P
Scale efficiency (TE_{crs}/TE_{vrs})	Y*M/Y*I	X*P/X*L

Appendix A-4. Estimation of stochastic production frontier for Hawaii swine producers.

Following the standard assumption of Zellner et al. (1966) that farmers maximize expected profits, the single-equation Cobb-Douglas stochastic production model (Aigner et al. 1977 and Meeusen and van den Broeck 1977) is specified as:

$$y_i = \beta_0 \prod_{k=1}^{4} x_{ik}^{\beta_k} e^{v_i - u_i}$$

Or equivalently,

$$\mathrm{Ln}y_i = \mathrm{Ln}\beta_0 + \beta_1 \mathrm{Ln}x_{i1} + \beta_2 \mathrm{Ln}x_{i2} + \beta_3 \mathrm{Ln}x_{i3} + \beta_4 \mathrm{Ln}x_{i4} + v_i - u_i \quad (8)$$

where y_i is annual live hog production of the i[th] farm measured in hundredweight (cwt) adjusted for price (Eq. 1); x_1 is annual consumption of purchased swine concentrates in tons; x_2 is annual hired and family labor measured in worker days, x_3 is annual other variable costs measured in \$1,000; x_4 is annual fixed costs including total fixed cash costs, depreciation, and cost of owner capital measured in \$1,000; β_k (k = 0, 1, 2, 3, 4) are the parameters to be estimated; v_is are assumed to be independently and identically distributed (iid) N(0, σv^2) random errors, independently distributed of the u_is; and u_is are non-negative random variables, associated with technical inefficiency, which are assumed to have half-normal distribution ($|N(0, \sigma u^2)|$). Using Battese and Coelli (1992) parametric specification, the maximum likelihood estimation of Eq. (8) provides the estimators for β, $\sigma^2 = \sigma^2_y + \sigma^2_u$, and $\gamma = \sigma^2_u + \sigma^2$. Given these assumptions, the prediction of technical efficiencies is based on conditional expectation of $\exp(-u_i)$, given the value of random variables, $\varepsilon_i = v_i - u_i$, i.e., $E(\exp(-u_i)/e_i)$. Subtracting $\exp(-v_i)$ from both sides of Eq. (8) we obtain

$$y_i^* = y_i - e^{-v_i}$$

Or equivalently,

$$\mathrm{Ln}y_i^* = \mathrm{Ln}y_i - v_i \qquad (9)$$

where y_i^* is the i^{th} firm's observed output adjusted for statistical noise. Then Eq. (9) forms the basis for deriving the technically efficient vector $\mathbf{x}_t$ and for analytically deriving the cost frontier. The analytically derived cost function which becomes the basis for deriving the economically efficient vector $\mathbf{x}_e$ is given (see Sharma 1996 for detail) as:

$$C(\mathbf{w}, y^*) = 1/(\beta_0^{1/\lambda}) \cdot \lambda / (\prod_{i=1}^{4} \beta_i^{\beta_i/\lambda}) \cdot \prod_{i=1}^{4} w_i^{\beta_i/\lambda} \cdot y^{*1/\lambda}$$

Or equivalently,

$$\mathrm{Ln}C = \mathrm{Ln}\theta_0 + \theta_1 \mathrm{Ln}w_1 + \theta_2 \mathrm{Ln}w_2 + \theta_3 \mathrm{Ln}w_3 + \theta_4 \mathrm{Ln}w_4 + \theta_5 \mathrm{Ln}y^* \qquad (10)$$

where $\mathbf{w}$ is the input price vector,

$\theta_0 = 1/(\beta_0^{1/\lambda}).\lambda/(\prod_{i=1}^{4}\beta_i^{\beta_i/\lambda})$, $\theta_i = \beta_i/\lambda (i = 1,...,4)$, $\theta_5 = 1/\lambda$,

and $\lambda = \beta_1 + \beta_2 + \beta_3 + \beta_4$.

The stochastic production frontier was estimated using the maximum likelihood (ML) method of FRONTIER 4.1 (Coelli 1994), and parameter estimates are presented in Appendix Table A-3. Parameter estimates presented here are based on the half-normal distribution for the inefficiency component. The corresponding values for the truncated normal distribution are presented in Sharma (1996). For comparison purposes, ordinary least squares (OLS) estimates are also included. The OLS and ML slope parameters are quite similar, suggesting that the frontier function is a neutral upward shift of the average OLS function. As shown by the insignificant F-statistic, the hypothesis of constant returns to scale based on restricted least squares could not be rejected.

The dual cost frontier derived algebraically from the stochastic production frontier for the half-normal distribution of the inefficiency component is as follows:

$$\mathrm{Ln}C = -1.218 + 0.353\mathrm{Ln}w_1 + 0.295\mathrm{Ln}w_2 + 0.292\mathrm{Ln}w_3 + 0.060\,\mathrm{Ln}w_4 + 0.959\mathrm{Ln}y^* \qquad (11)$$

where C is total cost of swine production, w_1 is the price of purchased concentrates (\$/ton), w_2 is the daily wage per worker (\$/day), w_3 is the price of other variable inputs set at 9.1% (the average interest rate for borrowed money during the last five years), w_4 is the price of fixed inputs set at 7.8% (the average interest rate on all borrowed capital), and y* is annual hog production in hundredweight adjusted for price and stochastic noise (Eqs. 1 and 9).

Appendix Table A-3. Estimates of average (OLS) Cobb-Douglas production function and maximum likelihood (ML) estimates of Cobb-Douglas stochastic production frontier.

Variable	Mean	OLS production function estimates	ML production frontier estimates
Intercept	-	2.20***	2.58**
		(0.57)	(0.55)
Feed (tons)	221.5	0.39***	0.37***
	[316.2]	(0.07)	(0.07)
Labor(person days)	619.2	0.29***	0.31***
	[425.4]	(0.10)	(0.10)
Other variable cost	31.6	0.29***	0.31***
($1,000)	[56.1]	(0.09)	(0.08)
Fixed cost	25.4	0.08	0.06
($1,000)	[43.9]	(0.09)	(0.09)
F-statistic CRS[a]	-	0.27	-
Adjusted R^2	-	0.85	-
γ	-	-	0.70**
			(0.25)
σ^2	-	-	0.38**
			(0.15)
Log likelihood	-	– 33.917	– 33.386
Mean of $\exp(-u_i)$	-	-	0.694
			[0.127]

***Significant at 1% level, **significant at 5%.
Figures in square brackets denote standard deviations and those in parentheses denote standard errors.
aCRS stands for constant returns to scale.

Appendix A-5. Estimation of DEA models for Hawaii swine producers

The DEA production frontiers were specified for the same output and input variables as in the stochastic production frontier. Among various DEA models, standard variable returns to scale (VRS) and constant returns to scale (CRS) input-oriented and output-oriented envelopment surfaces were estimated. VRS models produce the measures for pure technical efficiency and CRS models produce the measures for overall technical efficiency. The ratio of the CRS efficiency score to the VRS efficiency score gives the measure of scale efficiency. The models to be estimated are given below.

VRS input-oriented model (12)

First stage:

$$\text{VRS}(y_l, \mathbf{x}_l): \min_{\theta,\lambda_j,s,e_i} \theta$$

$$\text{subject to: } \sum_{j=1}^{53}\lambda_j y_j - s = y_l$$

$$-\sum_{j=1}^{53}\lambda_j x_{ij} + \theta x_{il} - e_i = 0 \quad i = 1, 2, 3, 4, \text{ inputs;}$$

$$\sum_{j=1}^{53}\lambda_j = 1 \quad ; \quad j = 1,2, \ldots, 53 \text{ DMUs;}$$

$$\lambda_j \geq 0;\ s \geq 0;\ e_i \geq 0.$$

Second stage:

$$\text{VRS}_E(y_l, \theta^l \mathbf{x}_l): \min_{\lambda_j,s,e_i} - [s + \sum_{i=1}^{4} e_i]$$

$$\text{subject to: } \sum_{j=1}^{53}\lambda_j y_j - s = y_l$$

$$-\sum_{j=1}^{53}\lambda_j x_{ij} + \theta^l x_{il} - e_i = 0 \quad i = 1, 2, 3, 4 \text{ inputs;}$$

$$\sum_{j=1}^{53}\lambda_j = 1 \ ;$$

$$\lambda_j \geq 0;\ s \geq 0;\ e_i \geq 0;$$

where, y_j output of j^{th} DMU $j = 1, \ldots, 53$ farms;
output = annual live hog production in cwt
x_{ij} i^{th} input of j^{th} DMU $i = 1, 2, 3, 4$ inputs;
1 = annual feed consumption in tons
2 = annual labor use in worker days
3 = annual other variable cost in \$1,000
4 = annual fixed cost in \$1,000
s output slack;
e_i i^{th} input excess;
λ_j weight of j^{th} DMU; and
θ^l is the solution to the first-stage problem.

VRS output-oriented model (13)

First stage:

$$\text{VRS}^O(y_l, \mathbf{x}_l): \max_{\phi,\lambda_j,s,e_i} \phi$$

$$\text{subject to: } \sum_{j=1}^{53}\lambda_j y_j - \phi y_l - s = 0 \quad ;$$

$$\sum_{j=1}^{53}\lambda_j x_{ij} + e_i = x_{il} \quad i = 1, \ldots, 4 \text{ inputs;}$$

$$\sum_{j=1}^{53}\lambda_j = 1 \quad ; \text{ and}$$

$$\lambda_j \geq 0;\ s \geq 0;\ e_i \geq 0.$$

Second stage:

$$\text{VRS}_E(\phi^l y_l, x_l): \min_{\lambda_j,s,e_i} - [s + \sum_{i=1}^{4} e_i]$$

$$\text{subject to: } \sum_{j=1}^{53}\lambda_j y_j - \phi^l y_l - s = 0 \quad ;$$

$$\sum_{j=1}^{53}\lambda_j x_{ij} + e_i = x_{il} \quad i = 1, \ldots, 4 \text{ inputs;}$$

$$\sum_{j=1}^{53}\lambda_j = 1 \quad ; \text{ and}$$

$$\lambda_j \geq 0;\ s \geq 0;\ e_i \geq 0.$$

The corresponding CRS models are obtained by dropping the constraint $\sum_{j=1}^{n}\lambda_j = 1$, and NIRS models are obtained by replacing that constraint with $\sum_{j=1}^{n}\lambda_j \leq 1$.

Appendix Table B-1. Average observed and technically and economically efficient input vectors.

Input/Farm size	Observed	Technically efficient	Economically efficient
Feed (Tons)			
> 75 sows	509.44	381.68	256.99
25–75 sows	78.06	52.03	44.04
< 25 sows	38.33	26.41	27.24
All farms	221.46	162.95	115.62
Labor (Person days)			
> 75 sows	899.74	676.73	892.76
25–75 sows	597.65	372.50	215.91
< 25 sows	290.77	214.39	129.00
All farms	619.09	436.81	433.96
Other variable inputs ($1,000)			
> 75 sows	67.43	52.09	54.08
25–75 sows	10.57	6.49	10.86
< 25 sows	12.70	8.92	6.52
All farms	31.56	23.52	25.13
Fixed inputs ($1,000)			
> 75 sows	51.27	37.63	11.21
25–75 sows	13.36	8.91	2.25
< 25 sows	7.74	5.47	1.35
All farms	25.37	18.23	5.20

Appendix Table B-2. Average observed input and technically and economically efficient input vectors for grain feeders and garbage feeders.

	Grain feeders			Garbage feeders		
Input / Farm size	Observed	Technically efficient	Economically efficient	Observed	Technically efficient	Economically efficient
Feed (Tons)						
> 75 sows	607.26	453.97	303.84	142.58	110.58	81.28
25–75 sows	124.89	86.47	57.75	50.75	31.93	36.04
< 25 sows	58.35	39.70	35.42	8.30	6.57	14.97
All farms	338.97	250.72	170.34	55.87	39.29	38.52
Labor (Person days)						
> 75 sows	950.73	709.71	1,010.90	708.50	553.06	449.74
25–75 sows	455.00	306.08	234.14	680.88	411.25	205.27
< 25 sows	213.06	140.71	152.04	407.33	324.91	94.45
All farms	624.63	453.37	586.15	611.30	413.48	219.50
Other variable inputs ($1,000)						
> 75 sows	81.26	62.82	62.49	15.56	11.84	22.53
25–75 sows	7.25	4.98	11.81	12.51	7.37	10.30
< 25 sows	18.74	12.91	7.70	3.66	2.93	4.76
All farms	46.40	35.27	35.14	10.65	6.97	11.02
Fixed inputs ($1,000)						
> 75 sows	58.53	42.68	12.95	24.05	18.70	4.67
25–75 sows	18.24	13.25	2.45	10.51	6.34	2.14
< 25 sows	7.88	5.11	1.60	7.61	6.02	0.99
All farms	34.73	25.13	7.28	12.18	8.52	2.28

Appendix Table B-3. Average cost savings at full efficiency level based on input-oriented DEA results for grain feeders and garbage feeders.

	Farm size			
	> 75 sows	25–75 sows	< 25 sows	All farms
Grain feeders				
No. of grain feeders analyzed	15	7	9	31
Average for sample grain feeders ($1,000)				
Observed economic cost	371.24	84.49	55.39	214.79
Observed net return	86.26	– 9.83	– 10.35	36.51
Cost saved at full efficiency[a]	98.14	37.52	23.30	62.72
Net return at full efficiency	184.40	27.69	12.95	99.23
Costs saved by input categories (% of total savings)				
Feed	40.6	26.8	19.3	36.5
Labor	15.1	36.6	13.6	17.8
Other variable inputs	13.3	5.9	51.0	16.3
Fixed inputs	31.0	30.7	16.1	29.4
Garbage feeders				
No. of garbage feeders analyzed	4	12	6	22
Average for sample garbage feeders ($1,000)				
Observed economic cost	129.10	79.02	37.49	76.80
Observed net return	44.44	– 21.50	– 4.30	– 4.82
Cost saved at full efficiency[a]	36.19	44.62	14.11	34.77
Net return at full efficiency	80.63	23.12	9.70	29.95
Costs saved by input categories (% of total savings)				
Feed	52.5	26.5	10.6	29.7
Labor	17.5	44.3	52.7	40.1
Other variable inputs	10.9	17.2	8.1	15.0
Fixed inputs	19.2	12.0	28.6	15.2

[a]Cost savings could not be decomposed into savings due to pure technical efficiency and those due to scale efficiency because pure technical efficiency score (TE_{VRS}) was smaller than overall technical efficiency score (TE_{CRS}) for some units, thus violating the formula to compute scale efficiency, $0 < TE_{CRS}/TE_{VRS} \leq 1$. This may be due to a smaller sample size when the DEA models were estimated separately for grain feeders and garbage feeders.

Appendix Table B-4. Average observed and projected input vectors and input-specific efficiency[a] estimates among all inefficient producers based on input-oriented DEA results.

	Farm size			
	> 75 sows	25–75 sows	< 25 sows	All farms
No. of inefficient producers[b]	14	17	12	43
Feed				
Observed (tons)	571.34	78.44	42.99	229.03
Projected (tons)	393.22	40.62	28.52	152.04
Efficiency (%)[c]	66.2	46.1	54.2	54.9
Labor				
Observed (person days)	967.14	635.53	265.50	640.23
Projected (person days)	694.78	271.17	134.56	370.97
Efficiency (%)	69.9	44.5	50.7	54.7
Other variable inputs				
Observed ($1,000)	62.26	10.43	15.25	28.65
Projected ($1,000)	46.42	4.02	4.98	18.09
Efficiency (%)	68.4	41.9	44.4	51.2
Fixed inputs				
Observed ($1,000)	61.92	13.26	8.66	27.82
Projected ($1,000)	29.92	4.57	2.58	12.27
Efficiency (%)	58.1	41.3	37.6	45.8

[a]Input-specific efficiency scores are computed as: Projected input ÷ Observed input X 100%

[b]The number of inefficient grain feeders (Appendix Table B-5) and the number of inefficient garbage feeders (Appendix Table B-6) do not add up to the number of all inefficient producers in this table because these numbers are based on three different frontiers.

[c]Note that efficiency scores are the averages of individual producers and hence do not equal to the ratio of average projected input to average observed input.

Appendix Table B-5. Average observed and projected input vectors and input-specific efficiency[a] estimates among inefficient grain feeders based on input-oriented DEA results.

	Farm size			
	> 75 sows	25–75 sows	< 25 sows	All farms
No. of inefficient grain feeders	12	6	6	24
Feed				
Observed (tons)	634.83	131.75	77.23	369.66
Projected (tons)	444.36	88.67	55.88	258.32
Efficiency (%)[b]	71.2	70.3	60.8	68.4
Labor				
Observed (person days)	1,011.33	514.67	211.3	687.17
Projected (person days)	749.52	226.01	127.63	463.17
Efficiency (%)	73.4	48.5	61.9	64.3
Other variable inputs				
Observed ($1,000)	69.67	8.18	26.91	43.61
Projected ($1,000)	53.38	5.61	9.10	30.37
Efficiency (%)	75.5	70.3	54.6	69.0
Fixed inputs				
Observed ($1,000)	67.52	16.31	9.19	40.88
Projected ($1,000)	29.46	5.85	3.55	17.08
Efficiency (%)	56.7	56.7	50.3	55.1

[a]Input-specific efficiency scores are computed as: Projected input ÷ Observed input X 100%

[b]Note that efficiency scores are the averages of individual producers and hence do not equal to the ratio of average projected input to average observed input.

Appendix Table B-6. Average observed and projected input vectors and input-specific efficiency[a] estimates among inefficient garbage feeders based on input-oriented DEA results.

	Farm size			
	> 75 sows	25–75 sows	< 25 sows	All farms
No. of inefficient garbage feeders	2	11	4	17
Feed				
Observed (tons)	190.35	49.36	9.68	56.61
Projected (tons)	78.28	14.35	4.82	19.63
Efficiency (%)[b]	40.1	32.9	50.1	37.8
Labor				
Observed (person days)	702.00	701.45	408.00	632.47
Projected (person days)	473.11	307.70	207.09	303.49
Efficiency (%)	61.5	44.9	50.0	48.1
Other variable inputs				
Observed ($1,000)	17.81	11.66	3.75	10.52
Projected ($1,000)	9.95	3.31	2.05	3.79
Efficiency (%)	50.7	30.9	53.8	38.6
Fixed inputs				
Observed ($1,000)	28.36	9.97	9.08	11.92
Projected ($1,000)	14.47	4.11	3.03	5.07
Efficiency (%)	46.4	43.5	38.8	42.7

[a]Input-specific efficiency scores are computed as: Projected input ÷ Observed input X 100%
[b]Note that efficiency scores are the averages of individual producers and hence do not equal to the ratio of average projected input to average observed input.

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